IET Intelligent Transport Systems

WILEY

The Institution of Engineering and Technology

ORIGINAL RESEARCH OPEN ACCESS

Analysing Traffic Accidents in Terms of Driver Violation Behaviour Types: Machine Learning and Sensitivity Analysis Approaches

Emre Kuşkapan[1] | Muhammed Yasin Çodur[2] | Dilum Dissanayake[3]

[1]Department of Civil Engineering/Transportation, Erzurum Technical University, Erzurum, Turkey | [2]College of Engineering and Technology, American University of the Middle East, Kuwait | [3]School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, UK

Correspondence: Emre Kuşkapan (emre.kuskapan@erzurum.edu.tr) | Dilum Dissanayake (d.dissanayake@bham.ac.uk)

Received: 21 February 2025 | **Revised:** 23 May 2025 | **Accepted:** 13 June 2025

Funding: The authors received no specific funding for this work.

ABSTRACT

Traffic accidents have become a major concern for governments, organizations and individuals worldwide due to the material and moral losses they cause. It is possible to reduce this concern by taking into account the research conducted by relevant institutions and organizations in this field. The main objective of this study is to categorize traffic accidents according to driver violation types and analyse them using machine learning algorithms and feature sensitivity to identify the most influential variables in each category. For this purpose, traffic accident reports that occurred in Erzurum province in the last 1 year were used to categorize and classify driver violation behaviour types. Five different machine learning algorithms, namely k-nearest neighbour, support vector machines, naive Bayes, multilayer perception and random forest, were used to examine the success performance of the classification. Among these, 91% successful classification was obtained with the random forest algorithm. Based on the classification obtained from this algorithm, sensitivity analysis was used to reveal the variables that most affect each violation category. The results of the analysis revealed that driver age and vehicle type were the most influential variables for many types of violations. Thanks to this study, the problems were clearly identified by going into the details of driver violation behaviours. At the end of the study, measures to reduce driver violation behaviours were proposed. If the recommendations that can reduce driver behaviour are taken into consideration by transportation authorities and policy makers, traffic accidents can be significantly reduced.

1 | Introduction

Traffic crashes have become a major concern for governments, organizations, and individuals around the world. According to the World Health Organization, road traffic crashes are a leading cause of death worldwide, with more than 1.3 million deaths recorded annually [1]. Road traffic crashes cause deaths and injuries, as well as significant economic losses and social disruption. Among the factors contributing to road traffic crashes, human factors account for approximately 93%. Among these, drivers are in the first place by causing approximately 89% of traffic accidents [2–6]. Driver-related accidents are directly related to the driver's compliance with traffic rules. Violations of traffic rules on the existing road section significantly increase the risk of traffic accidents.

In order to better examine the traffic accidents that occur, these accidents need to be analysed. By clearly identifying the violations that cause accidents and taking measures accordingly, traffic accidents can be significantly reduced. Although traditional

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2025 The Author(s). *IET Intelligent Transport Systems* published by John Wiley & Sons Ltd on behalf of The Institution of Engineering and Technology.

methods have been used to analyse traffic crashes in the past, new methods have been developed with the development of technology. Traditionally, traffic crash analysis has relied on manual review of crash reports and data collected from a variety of sources such as closed-circuit television (CCTV) cameras, weather sensors and traffic flow sensors [7–10]. However, with advances in technology and the availability of large amounts of data, artificial intelligence techniques have emerged as a promising approach to analyse traffic accidents and identify their causes. Since artificial intelligence includes methods such as deep learning, machine learning and data mining, it enables the analysis process to be done faster and with higher accuracy.

Machine learning is one of the most frequently used artificial intelligence methods for analysing traffic accidents. Machine learning has a large number of algorithms that incorporate various methods of analysing data [6, 11–14]. These algorithms can analyse large amounts of data and identify patterns that can be used to predict the likelihood of traffic accidents and understand the underlying factors that contribute to them. These algorithms can also help identify high-risk areas, which can be useful for preventing accidents on a point-by-point basis. In order to further elaborate on how this method can contribute to the analysis of traffic accidents, it is necessary to review the existing studies in the literature.

2 | Related Work

There are various studies in the literature that use machine learning to analyse traffic accidents. One of the most preferred types of studies in this field is the analysis of traffic accidents by classifying them with machine learning methods. When the existing studies in the literature on the analysis and classification of traffic accidents with machine learning are examined in general, studies on three categories stand out more:

- Analysis of traffic accident hot points [15–18].
- Severity analysis of traffic accidents [19–23].
- Prediction of traffic accidents [24–27].

Thanks to the success of machine learning algorithms in classifying data, it can become easier to analyse traffic accidents. In particular, the classification of data into certain classes allows the analyst to make a more comprehensive analysis. In this way, the number of studies analysing traffic accidents from different aspects is increasing. In one of the studies conducted in this field, Theofilatos et al. [28] compared the results by predicting the effect of real-time traffic and weather parameters on highway accidents with machine learning and deep learning models. As a result of the study, they found that the deep learning model gave more balanced results than machine learning, as well as the naive Bayes algorithm, which is a machine learning algorithm, showing good performance.

Santos et al. [29] aimed to reduce the damages and severity of accidents that may occur by utilizing data on traffic accidents that occurred between 2016 and 2019 in the Setúbal region of Portugal. For this reason, the severity of traffic accidents was analysed with machine learning algorithms. The results show that a rule-based model using the C5.0 algorithm is able to accurately identify the most relevant factors that define the severity of a traffic accident.

In another study in this field, Ma et al. [30] mentioned the importance of accurately predicting accidents caused by driver distraction. For this purpose, they analysed the relationship between driver's phone use and distraction using machine learning. As a result of their analyses, they concluded that cell phone use is an important factor in distraction and that distraction-related traffic accidents are more likely to occur on highway segments with irregular traffic flow conditions or medium truck volumes.

Nassiri and Mohamadian [31] emphasized that traffic accident frequency prediction is an important tool in traffic management. They used machine learning methods such as negative binomial regression, zero inflated negative binomial regression, support vector machine and back-propagation neural network models for accident frequency prediction. As a result of the analysis, they revealed that the prediction capability of the negative binomial regression algorithm is better.

Bokaba et al. [32] mentioned that the use of classification features of machine learning has increased in recent years in order to better analyse the causes and effects of traffic accidents. For this reason, in their study, it was aimed to obtain the most suitable algorithm for the dataset by using different machine learning algorithms. In the results of the analysis, it was revealed that the random forest algorithm obtained the most successful results. According to the results obtained from this algorithm, a traffic accident prediction model was created.

Considering the studies specific to driver violations: Xu et al. [33] used a driving simulator to design driving scenarios and study the driving performance of drivers with different driving experiences when other road users violate traffic rules. The experimental results showed that some novice drivers ignored the position of their own vehicles when they encountered traffic violations, leading to collisions with other road users. Khattak et al. [34] developed a systematic taxonomy of driver errors and violations to examine the role of human factors and improve accident investigations. Based on the data obtained, built environments (measured by road zones) were classified according to road functional classification and land uses. For example, residential areas, school zones and church zones. According to the calculation of the percentage of accidents in a given area based on the basic percentage, interstate roads and open rural/open residential areas (rural and semi-rural settlements) may pose lower risks, while urban, business/industrial and school zone locations showed higher accident risks. Ortega et al. [35] examined the effects of cell phone use on drivers with the help of a simulator. The findings confirmed that there are significant differences in the driving performance of young drivers in terms of vehicle control (i.e., lateral distance and hard shoulder line violations) between inattentive and non-attentive drivers. Moreover, the overall workload score of young drivers was found to increase with their use of cell phones while driving.

This study addresses the gap in the literature regarding the lack of categorization of driver-related traffic violations in the context of traffic accidents using machine learning and sensitivity analysis

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

methods. Categorization of driver violations allows for a more efficient interpretation of traffic accidents. Machine learning algorithms were used to successfully perform this categorization process. According to the results obtained from the most successful algorithm for the available data set, sensitivity analysis was performed, and the most effective factors for each type of traffic violation were determined. The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of the relevant literature, focusing on previous research on traffic accidents, driver behaviour, and machine learning applications. Section 3 details the dataset used in the study, outlines the preprocessing steps, and explains the methodology, including the machine learning algorithms and the sensitivity analysis approach. Section 4 presents empirical results, followed by a discussion of their implications in the context of existing studies. Finally, Section 5 summarizes the main findings, outlines the study's limitations, and suggests directions for future research.

3 | Material and Method

3.1 | Case Study and Data Description

Erzurum, a city located in the eastern region of Turkey, has a relatively well-developed transportation infrastructure. The city is connected to other parts of Turkey and neighbouring countries through different modes of transportation, including air, road, and rail. Road transportation is the main mode of transportation in Erzurum, and the city is connected to other parts of Turkey by well-developed highways. Erzurum is located on the important highway connecting Ankara, the capital of Turkey, to the eastern region of the country, and it is also connected to other cities in the region by smaller highways [36].

According to 2022 statistics, Erzurum ranks in the top two among the provinces of the Northeastern Anatolia Region in terms of the number of traffic accidents with fatalities and injuries, the number of traffic accidents with material damage, the number of traffic accidents with fatalities and the number of traffic accidents with injuries [37, 38]. It is very important to analyse the traffic accidents that occur in the city and to go into the details of the causes of these accidents to reduce traffic accidents both in the city and in the region. An accident density map was created in the ArcGIS program by using the coordinates of traffic accidents with death or injury that occurred in the city in 2022. The coordinates of these traffic accidents that occurred in the city in 2022 and the accident density map are shown in Figure 1.

Traffic crashes that occur in the city and result in death, injury or serious damage are recorded by the traffic police. These crash records, along with all their details, are collected at the Erzurum Metropolitan Municipality Traffic Department for various investigations. The details of the crashes include characteristics of the drivers, passengers and pedestrians, as well as environmental factors and road conditions. As of 2022, a total of 6892 traffic accidents occurred in Erzurum. Of the accidents in the city, 1121 were fatal or injury accidents. In addition, a total of 50 people died because of these accidents. In this study, traffic accidents occurring in urban areas are analysed. Because most of the accidents occurred in the city centre and on the main roads connecting to this centre. By studying the crashes that occur in the city, it has been found that approximately 90% of them are caused by traffic violations by the driver. Table 1 below provides

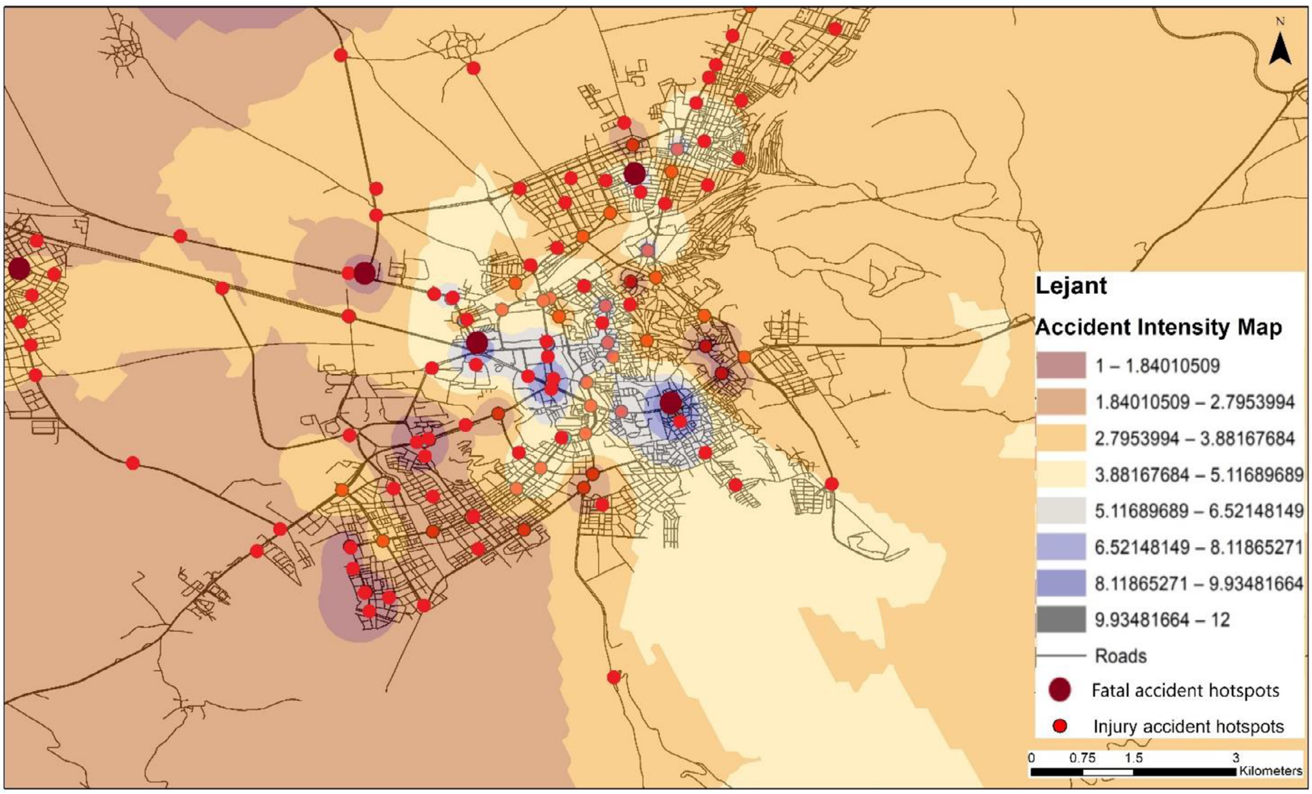

FIGURE 1 | Coordinates of crashes that occurred in the city in 2022.

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 | Details of some traffic accidents in the city.

Accident number	X coordinate	Y coordinate	Day of week	Time of day	Type of road	Pedestrian crossing	Shoulder (road)	Traffic light or sign	Weather	Type of road surface	Type of vehicle	Fuel type	Age of driver	Educational level of the driver	Type of violation
41	41.280	39.052	Sun	18:15	3	2	2	3	1	1	7	2	40	6	56/1-C
42	41.259	39.896	Mon	10:47	1	1	1	1	1	1	5	1	46	6	52/1-A
44	41.153	39.932	Mon	15:45	3	1	2	3	1	1	5	2	22	4	57/1-A
45	41.258	39.907	Tue	22:50	1	1	1	3	2	1	7	2	45	6	53/1-B
46	41.286	39.909	Wed	15:50	1	1	1	3	2	2	5	2	61	6	46/2-B
47	41.257	39.904	Wed	17:25	1	2	2	1	2	2	10	1	35	6	51/2-B
48	41.253	39.904	Thu	09:54	1	2	1	1	1	2	5	2	23	5	52/1-B
48	41.271	39.930	Fri	10:00	1	1	2	3	1	1	5	2	23	6	52/1-A
49	41.274	39.911	Fri	17:30	1	1	2	3	1	1	10	2	36	6	52/1-B
51	41.268	39.888	Sat	11:25	1	1	2	3	1	1	5	3	64	1	57/1-B
52	41.262	39.906	Sat	16:40	1	1	2	3	1	2	5	2	35	5	57/1-B
53	41.297	39.900	Sun	15:15	1	1	2	2	1	4	5	3	21	6	57/1-C
55	41.951	39.554	Mon	13:30	1	1	1	1	1	1	7	2	29	5	47/1-B
56	41.184	39.916	Mon	19:32	1	1	2	3	1	1	5	2	22	2	52/1-B
57	41.238	39.898	Tue	15:15	1	1	1	1	4	2	5	2	28	6	47/1-B
58	41.248	39.880	Tue	23:00	1	1	2	3	4	3	7	2	23	6	46/2-C
59	41.204	39.924	Wed	08:40	1	1	2	3	4	2	5	3	25	4	57/1-A
60	41.273	39.906	Wed	12:10	1	1	2	2	1	2	5	2	29	4	74
61	41.253	39.903	Wed	18:10	1	1	2	1	4	2	5	2	37	4	52/1-B
62	41.259	39.905	Thu	20:20	1	1	1	1	1	4	5	1	23	6	59/A
63	41.267	39.901	Fri	08:30	3	1	2	3	4	3	5	2	31	5	Y.145/B
64	41.272	39.928	Fri	16:20	1	1	1	3	1	3	6	1	41	5	74
65	41.241	39.890	Sun	00:30	1	1	2	3	1	6	5	3	34	3	52/1-B

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

details of some of the traffic accidents that occurred in the city in 2022 and information on which driver violations were responsible for these accidents.

Each dataset contains information such as the coordinates where the accident occurred, the time of the accident, weather and road surface conditions, absence of traffic lights and signs, vehicle characteristics, age and education level of the driver, and type of traffic violation. The categorical data in the dataset were converted into numerical form by numbering. The classes in each data are numbered starting from one. If there are two states for a category, one means present and two means absent. Pedestrian crossings and shoulder categories are examples of this situation. For the road type category, there are three classes: divided road, one-way road and two-way road. For the category of traffic lights or signs, there are three classes: present, absent and inappropriate, respectively. For the weather category, there are six classes: clear, fog/smoke, rain, snow, hail and strong wind, respectively. For the road surface category, there are five classes: dry, wet/moist, snowy, icy and other. For the vehicle type category, there are fifteen classes: bicycle, horse-drawn carriage, motorized bicycle, motorcycle, automobile, minibus, van, truck, tow truck, bus, tractor, off-road vehicle, construction equipment, ambulance and other. For the fuel type category, there are four classes: gasoline, diesel, LPG, and electric. For the driver's education level category, there are six classes as primary school, secondary school, elementary school, high school, undergraduate and postgraduate, respectively.

When all reports of traffic accidents are examined in detail, it is determined that driver violations vary. A total of 34 different traffic violations were detected in all the crashes by the traffic police of the Police Department in accordance with the Highway Traffic Law [39]. Some of these violations only result in accidents with material damage, while others can cause the death of many people. Table 2 shows the traffic violations committed by the drivers in the crashes that occurred in the city and the codes of these violations according to the Highway Traffic Law.

3.2 | Methodology

3.2.1 | Machine Learning

Machine learning is an area of artificial intelligence that enables computer systems to learn from data. This approach gives computers the ability to extract knowledge from experience, similar to how humans learn naturally. Machine learning algorithms analyse large amounts of data to identify patterns and relationships, enabling them to make predictions and decisions. Two basic approaches, supervised and unsupervised learning, form the foundation of machine learning. Supervised learning uses labelled training data to train models, while unsupervised learning aims to structure data without relying on labels. Machine learning has applications in diverse domains such as image recognition, natural language processing, classification, and prediction, touching many aspects of daily life [40, 41].

Machine learning allows the many algorithms it contains to look at the data set from different angles. Therefore, while one algorithm gives successful results for a data set, another algorithm may give unsuccessful results. In this study, various machine learning algorithms were used to successfully analyse the dataset. In this study, algorithms with different features, such as k-nearest neighbour (IBK), support vector machines (LIBSVM), naive Bayes (NB), multilayer perceptron (MP) and random forest (RF), were used to determine the most appropriate algorithm for the data set.

The IBK algorithm is a method based on majority voting of its nearest neighbour that is often used to classify or predict the label of an instance. When classifying a new instance, k-NN first finds its k nearest neighbours and then classifies it by voting for the categories of the k nearest neighbours. Therefore, an appropriate number of nearest neighbours is critical for a k-NN classifier [42].

LIBSVM are machine learning algorithms used for classification or regression tasks. It is a further improvement made on the SVM, which complements some parameters of the original SVM. LIBSVM aims to separate data points by constructing an optimal separating hyperplane. It has shown high performance in classification or regression problems [43–45].

NB is a simple but effective machine learning classification algorithm. Based on Bayes' theorem, it assumes independence between features when given a class label. It assumes that the presence of a particular feature of a class is unrelated to the presence of any other feature, given the class variable. Depending on the precise nature of the probability model, NB can be trained very efficiently in a supervised learning setting. The NB algorithm has achieved successful results in various applications, such as natural language processing, spam filtering, and sentiment analysis [46, 47].

The MP is one of the fundamental types of artificial neural networks. It consists of an input layer, hidden layers, and an output layer and uses weights and activation functions between these layers. This algorithm is commonly used to solve complex problems, such as deep learning and image processing [48–50].

RF is a machine learning algorithm that combines a set of decision trees to solve classification or regression problems. The algorithm, which combines several randomized decision trees and aggregates their predictions by averaging, shows excellent performance in settings where the number of variables is much larger than the number of observations. Each tree is constructed using random data sampling and random feature selection. RFs are used to achieve high accuracy and robustness in complex data sets [51, 52].

3.2.2 | Sensitivity Analysis

Sensitivity analysis examines the effect of changing coefficient values in a linear programming problem on the optimal solution of the problem. It is examined to what extent the coefficients in the model are imprecise and how much they will affect the optimal solution by changing later. If it is observed that there will be a difference in the optimal solution as a result of this change, the problem should be solved again [53, 54].

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | Driver-related traffic violation behaviours detected in the study area.

Violation code	Violation description
46/2-B	Changing lanes in a dangerous manner
46/2-C	Changing lanes in a way that changes the flow of traffic and endangers the safety of passengers, unless otherwise indicated by a sign
47/1-A	Disregard warning signs from police and other authorities
47/1-B	Running a red light
47/1-C	Disregard traffic signs
48/5	Driving under the influence of alcohol
51/2-B	Speed violation
52/1-A	Failure to reduce speed when approaching intersections
52/1-B	Failure to drive according to the traffic and road conditions
52/1-C	Failure to maintain a safe following distance
53/1-A	Failure to keep right
53/1-B	Failure to obey left turn rules
53/1-C	Failure to obey roundabout rules
53/2A	Failure to yield to pedestrians and bicyclists making right and left turns
54/1-A	Failure to obey the rules of passing when attempting to pass the vehicle in front
54/1-B	Making unsafe passing manoeuvres where passing is prohibited
56/1-A	Making lane violations
56/1-B	Failure to yield to oncoming traffic in two-way traffic situations
56/1-C	Failure to maintain a following distance from the vehicle in front
57/1-A	Failure to properly reduce speed and yield to other vehicles when approaching intersections
57/1-B	Failure to give priority to the main road at junctions with secondary roads
57/1-C	Drivers of non-motorized vehicles do not yield to motor vehicles coming from the right
57/1-D	Entering the intersection in such a way as to impede traffic in the opposite direction
57/1-E	Stopping, turning or slowing down unnecessarily at intersections
58/A	Failure to stop on the far right side of the road according to the direction of travel, failing to allow passengers to enter and exit from the right side of the road
59/A	Stopping unnecessarily on highways, except in emergencies
60/1-B	Parking in the left lane of the roadway
60/1-G	Stopping alongside parked or stopped vehicles on the roadway
65/1-I	Carrying unsecured cargo
67/A	Creating a hazard to other vehicles using the roadway when leaving a parked position
69/1A	Driving or causing to be driven domestic animals, herds, or manually operated vehicles without observing the rules of the road
74/A	Failure to yield to pedestrians in places where there are speed limits and pedestrian crossings
Y.110/B-3	Failure to yield to pedestrians at pedestrian crossings
Y.145/B	Intimidate or disturb other drivers

In sensitivity analysis, changes in the objective function, constraint coefficients and resource values are examined, as well as the change in the optimal solution if a new variable or a new constraint is added. Normally, it is possible to find the effects of any change in resources or constraints by re-solving the linear programming model. However, such a resolution is usually unnecessary. Because it is possible to arrive at a different optimal solution with the same basic variables. Sensitivity analysis tries to determine the effect of such changes from the optimal solution table without re-solving [55–58].

4 | Results and Discussion

A total of 714 accidents occurred in the study area in one year. Of these, 609 were reported as accidents caused by driver violations.

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 3 | Categories created for traffic violation behaviours.

Traffic violation categories	Violation codes
Speed violation	51/2-B, 52/1-A
Failure to obey traffic signs and officials	46/2-C, 47/1-A, 47/1-B, 47/1-C
Intersection use violations	53/1-A, 53/1-B, 53/1-C, 57/1-A, 57/1-D, 57/1-E
Failure to yield	53/2A, 56/1-B, 57/1-B, 57/1-C, 74/A, Y.110/B-3
Following distance violation	52/1-C, 56/1-C
Improper passing and lane violations	46/2-B, 54/1-A, 54/1-B, 56/1-A, 67/A
Disregarding traffic conditions	52/1-B
Disregard for traffic flow and order	48/5, 58/A, 59/A, 60/1-B, 60/1-G, 65/1-I, 69/1A, Y.145/B

This shows that approximately 85% of the total number of accidents were directly caused by drivers. These traffic violations were listed under 34 different traffic violation types. Since the large number of traffic violation types made it difficult to analyse the data, these types were divided into clusters according to their characteristics. In this clustering process, the main headings under which each traffic violation occurred were determined. For example, the types of traffic violations associated with the driver's speed violation were grouped together under the same main heading. When this process was done for all types of violations, a total of eight main headings were created. These main headings and the types of violations under these headings are shown in Table 3.

Each category created for traffic violations contains one or more traffic violations. The aim is to evaluate similar traffic violations together in the categories created. In this way, it became easier to analyse traffic violations. After the categorization process of traffic violations was completed, machine learning analysis was performed. In the machine learning analysis processes, accuracy, precision, recall, *f*-measure, kappa statistic, mean absolute error (MAE), and root mean square error (RMSE) variables are obtained. Of these variables, precision, accuracy, recall and *f*-measure are expressed as performance metrics, while kappa statistics, MAE and RMSE variables are expressed as error criteria. For an algorithm to be successful, performance metrics and kappa statistics should be high, while MAE and RMSE values should be low. In case of incompatibility between these variables, it can be said that the chosen algorithm is not suitable for the analysis of the existing data set. For this reason, five different machine learning algorithms were used in this study to obtain more efficient and accurate results. In this section, 10-fold cross-validation was used to ensure a reliable evaluation across all models. Figure 2 shows the performance metrics obtained by the algorithms.

When the performance metrics of the algorithms are examined, it is seen that RF is the most successful algorithm. The *f*-measure, recall and precision values obtained with this algorithm are very high compared to others. The second most successful algorithm for the current dataset is MP. Similar results were obtained by the LIBSVM and IBK algorithms. Among the algorithms, the algorithm with the lowest performance metric is NB.

After examining the performance metrics of the algorithms, it is necessary to examine the error criteria. Because from time to time, there can be an incompatibility between these two criteria. The compatibility of these two criteria indicates that the algorithm can successfully classify the given data set. The error criteria of the algorithms are shown in Figure 3.

Looking at the error criteria of the algorithms, the RF algorithm has the highest kappa statistics and the lowest MAE and RMSE values. Although the MAE value of the LIBSVM algorithm is low, the RMSE value is high, and the kappa statistic value is low. These results indicate that the LIBSVM algorithm is not suitable for the current data set. For the other three algorithms, the error measures have much more distant values than the RF algorithm. All these results show that the most suitable algorithm for the current dataset is the RF algorithm.

The classification of all violations according to the RF algorithm has been performed, and the distribution of driver violations in traffic crashes that have occurred in 2022 has been revealed. Considering the distribution of driver violations, it becomes possible to take various precautions in traffic and significantly reduce the number of crashes. Figure 4 shows the categorical distribution of 609 driver-related traffic crashes in one year in Erzurum province.

The top three categories of driver violation behaviours are speeding, disregard for traffic conditions and intersection use violations. Speeding is the biggest factor that increases the number of fatalities and severity of injuries in traffic crashes. This is because the speed limit set for a road section is the optimum speed for that section, considering environmental factors and road conditions. When determining these speed limits, the size and characteristics of the vehicle are considered, and it is aimed at stopping the vehicle safely from the moment the brakes are applied. If drivers do not take traffic conditions into account, they may jeopardize both their own safety and the safety of other people (passengers or pedestrians) in traffic.

Intersection use violations can sometimes cause traffic accidents as well as increase traffic congestion at the intersection. One of the most common cases of this type of violation is that when there is a change in the geometric design of the intersection, the drivers may behave in the same way as before out of frustration. Another common situation is the inability of drivers to use the intersection efficiently due to the type of intersection. For example, modern roundabouts do not have traffic lights. In these intersections, the vehicle inside the island has priority, and drivers who want to enter the intersection island from other roads have to behave accordingly. If this usage characteristic of the intersection is not known, violations of usage are common at these intersections.

Besides these three most common driver violations, other categories are also very important. These include erroneous overtaking, lane violations and failure to yield, which seriously

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

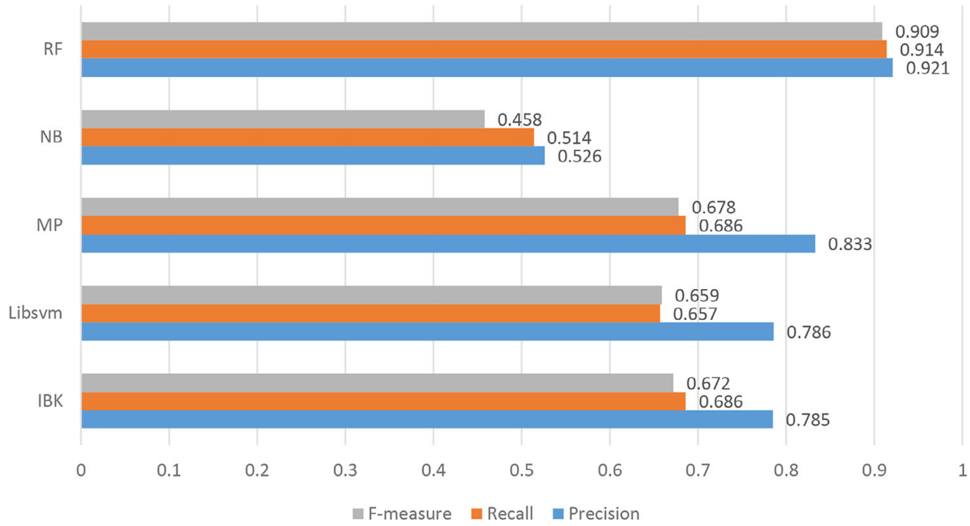

FIGURE 2 | Performance metrics obtained with algorithms.

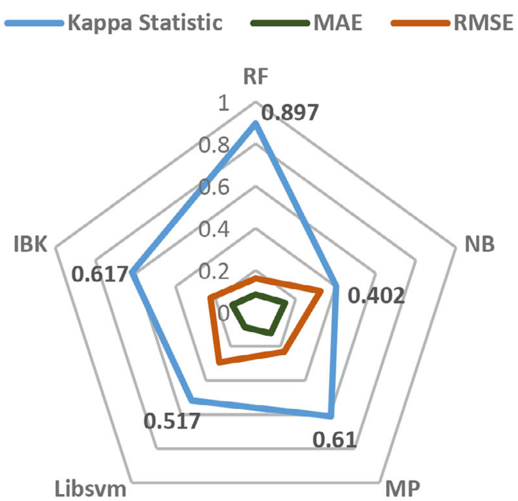

FIGURE 3 | Error criteria obtained from algorithms.

jeopardize pedestrian safety. On the other hand, failure to maintain the following distances between vehicles also leads to traffic accidents, often resulting in rear-end collisions.

In order to reveal the relationship between these traffic violation categories and the variables, a sensitivity analysis was conducted. According to this analysis, the three most influential variables in each traffic violation category and their impact ratios are shown in Table 4.

The results of the sensitivity analysis show that the age of the driver is the most influential factor in speed violations. A detailed analysis of the dataset reveals that drivers are more likely to commit speed violations when their age is between 20 and 38. In the case of failure to obey traffic signs and officials, the most influential variable is the educational level of drivers. Drivers with primary and secondary school education are more likely to commit this violation. In the case of intersection usage violations, the three most effective variables are time of day, pedestrian crossing and traffic light or sign. The most effective variable in failure to yield violations is the type of vehicle. Especially drivers driving minibuses were found to commit this violation more frequently. In following distance violations, the type of road surface was found to be the most determining variable. When the road surface is dry, accidents due to following distance violations are more frequent. The most effective variable in improper passing and lane violations was found to be the age of the driver. A detailed analysis of the data reveals that drivers between the ages of 30 and 43 are more prone to this type of violation. In the type of violation disregarding traffic conditions, it was determined that the education level of the driver and age of the driver have a near effect. Upon detailed analysis of the data, it was determined that drivers with secondary and high school education levels and between the ages of 23 and 40 were more prone to this type of violation. It has been determined that the most effective variable in the violation type of disregarding for traffic flow and order is the type of vehicle. When the data related to this situation were analysed, it was determined that minibus and pickup truck drivers were more prone to this type of violation.

When the results obtained are analysed in general, it is determined that different variables are effective for each type of violation in traffic accidents caused by driver violations. However, the age of the driver and vehicle type were found to be very effective variables in many types of violations. The age of the driver was found to be the most influential variable in speed violations, overtaking and lane violations and disregarding traffic conditions. Vehicle type was found to be the most influential variable in traffic flow and order violations and failure to yield. For this reason, it would be more useful to elaborate on traffic accidents by categorizing them as in this study, rather than just interpreting them in general.

The observation that younger drivers are more inclined to speeding violations aligns with previous studies, such as Ma et al. [30], who emphasized the role of age in distraction-related crashes. Similar findings were reported by Kuşkapan et al. [9], who identified age and gender as influential factors in the spatial clustering of fatal and injury crashes in Erzurum. Moreover, the effect of educational level on compliance with traffic rules is

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

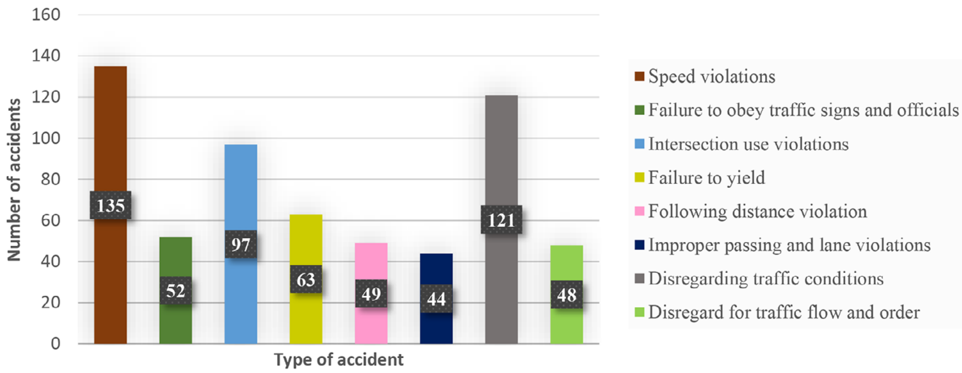

FIGURE 4 | Categorical distribution of driver-related traffic crashes.

TABLE 4 | Sensitivity analysis of traffic violation behaviour categories.

Traffic violation behaviour categories	Most efficient variables	Sensitivity analysis (%)
Speed violation	Type of vehicle	35
	Time of day	16
	Age of driver	37
Failure to obey traffic signs and officials	Educational level of the driver	29
	Pedestrian crossing	14
	Age of driver	21
Intersection use violations	Time of day	20
	Pedestrian crossing	17
	Traffic light or sign	20
Failure to yield	Type of vehicle	38
	Pedestrian crossing	17
	Type of road	13
Following distance violation	Fuel type	14
	Type of road surface	27
	Weather	18
Improper passing and lane violations	Type of vehicle	36
	Age of driver	41
	Day of week	17
Disregarding traffic conditions	Weather	14
	Educational level of the driver	28
	Age of driver	29
Disregard for traffic flow and order	Type of vehicle	40
	Time of day	11
	Type of road	13

consistent with Infante et al. [20] and is further supported by Kuşkapan et al. [17], who highlighted that driver characteristics significantly influence violation behaviour patterns in urban areas.

All driver violation behaviours categorized in the study cause serious material and moral losses for countries. For this reason, many developed countries have implemented various policies to minimize these violations. The most common of these policies is the level of deterrence of traffic fines. High fines or suspension of a driver's license for a certain period of time are important deterrents for traffic violations. It is recommended that these fines be increased by the local government and police in the study area. The most common speed violations by drivers in the

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

city can be prevented by using electronic monitoring systems. Various information and guidance can be provided through smart signs for traffic flow order and the proper use of intersections. In addition, seminars and talks can be organized to inform drivers that obeying traffic rules is a civic duty and that they should be tolerant of other people in traffic.

In addition to all these, it is necessary to increase the number of training courses on obeying traffic rules and not violating these rules in education systems, starting from primary school. It is possible to reduce traffic accidents by increasing people's sensitivity to the rules with more efficient training starting from this level.

5 | Conclusion

Most traffic crashes are caused by drivers who violate traffic laws. To reduce the number of crashes, a traffic fine is imposed for each type of violation. Since these fines are very diverse, it is difficult to analyse driver violation behaviours. In this study, all traffic fines were analysed, and a classification process was performed according to the types of fines. In the classification process, all traffic fines are classified into eight main categories according to their content. Machine learning algorithms were used to measure the success of this classification. Of the six different algorithms used in the study, the RF algorithm produced very successful results. As a result of the distribution made with this algorithm, it was found that speed violations, disregarding traffic conditions, and intersection use violations were the most common problems among 609 traffic crashes. To prevent these problems, it is recommended to use electronic monitoring systems that electronically monitor speed violations with cameras. For disregarding traffic conditions and intersection use violations, it is recommended that traffic police officers conduct inspections on road sections where these problems are common. To minimize all driver violations in general, it is recommended that traffic fines should be a deterrent. In this case, it is likely that the rate of drivers' compliance with traffic rules will increase.

In future studies to be conducted in this field, pedestrian and passenger violation behaviours can be handled similarly, and the human factor, which is the most effective factor in traffic accidents, can be addressed in terms of other variables. When all these situations are evaluated together, it is possible for policy makers to examine the results and make various policies to reduce human-caused traffic accidents.

Author Contributions

Emre Kuşkapan: conceptualisation, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, validation, visualisation, writing – original draft and editing. **Muhammed Yasin Çodur:** conceptualisation, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources. **Dilum Dissanayake:** supervision, validation, writing – original draft, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data will be made available on request.

References

1. "Road Traffic Injuries," World Health Organization, accessed February 24, 2024, https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries#:~:text=Roadtrafficinjuriesarethe,pedestrians%2C-cyclists%2Candmotorcyclist.

2. K. Alkaabi, "Identification of Hotspot Areas for Traffic Accidents and Analyzing Drivers' Behaviours and Road Accidents," *Transportation Research Interdisciplinary Perspectives* 22 (2023): 100929, https://doi.org/10.1016/j.trip.2023.100929.

3. "Traffic Safety," General Directorate of Security, accessed January12, 2024, https://www.guvenlitrafik.gov.tr/1-durum-degerlendirmesi.

4. A. Moradi, S. S. H. Nazari, and K. Rahmani, "Sleepiness and the Risk of Road Traffic Accidents: A Systematic Review and Meta-Analysis of Previous Studies," *Transportation Research Part F: Traffic Psychology and Behaviour* 65 (2019): 620–629, https://doi.org/10.1016/j.trf.2018.09.013.

5. S. E. J. Nasab, S. S. Naseralavi, and N. Pourmoallem, "Investigating the Influence of Vehicular Ad-hoc Networks on Driver Behaviours and Traffic Accidents," *Travel Behaviour and Society* 2, no. 3 (2015): 156–165, https://doi.org/10.1016/j.tbs.2015.01.001.

6. Z. Zhang, Q. He, J. Gao , and M. Ni, "A Deep Learning Approach for Detecting Traffic Accidents From Social Media Data," *Transportation Research Part C: Emerging Technologies* 86 (2018): 580–596, https://doi.org/10.1016/j.trc.2017.11.027.

7. N. Buch, S. A. Velastin, and J. Orwell, "A Review of Computer Vision Techniques for the Analysis of Urban Traffic," *IEEE Transactions on Intelligent Transportation Systems* 12, no. 3 (2011): 920–939, https://doi.org/10.1109/TITS.2011.2119372.

8. K. Kim, S. Gutesa, B. Dimitrijevic, et al., "Performance Evaluation of Video Analytics for Traffic Incident Detection and Vehicle Counts Collection," in *Recent Advances in Intelligent Image Search and Video Retrieval* (Springer, 2017), 213–231.

9. E. Kuşkapan, M. Y. Çodur, and A. Atalay, "Speed Violation Analysis of Heavy Vehicles on Highways Using Spatial Analysis and Machine Learning Algorithms," *Accident Analysis and Prevention* 155 (2021): 106098 https://doi.org/10.1016/j.aap.2021.106098.

10. H. Yang, Z. Wang, K. Xie, K. Ozbay, and M. Imprialou, "Methodological Evolution and Frontiers of Identifying, Modelling and Preventing Secondary Crashes on Highways," *Accident Analysis and Prevention* 117 (2018): 40–54, https://doi.org/10.1016/j.aap.2018.04.001.

11. Z. E. Abou Elassad, H. Mousannif, H. Al Moatassime, and A. Karkouch, "The Application of Machine Learning Techniques for Driving Behaviour Analysis: A Conceptual Framework and a Systematic Literature Review," *Engineering Applications of Artificial Intelligence* 87 (2020): 103312, https://doi.org/10.1016/j.engappai.2019.103312.

12. Z. Halim, R. Kalsoom, S. Bashir, and G. Abbas, "Artificial Intelligence Techniques for Driving Safety and Vehicle Crash Prediction," *Artificial Intelligence Review* 46 (2016): 351–387, https://doi.org/10.1007/s10462-016-9467-9.

13. P. Jing, Y. Cai, B. Wang, et al., "Listen to Social Media Users: Mining Chinese Public Perception of Automated Vehicles After Crashes," *Transportation Research Part F: Traffic Psychology and Behaviour* 93 (2023): 248–265, https://doi.org/10.1016/j.trf.2023.01.018.

14. Z. Ullah, F. Al-Turjman, L. Mostarda, and R. Gagliardi, "Applications of Artificial Intelligence and Machine Learning in Smart Cities," *Computer Communications* 154 (2020): 313–323, https://doi.org/10.1016/j.comcom.2020.02.069.

15. A. Atalay and A. Tortum, "According to Traffic Accidents Between 1997–2006 Years Clustering Analysis of Provinces in Turkey," *Pamukkale University Journal of Engineering Sciences* 16, no. 3 (2010): 335–343

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

16. U. Gupta, M. K. Varun, and G. Srinivasa, "A Comprehensive Study of Road Traffic Accidents: Hotspot Analysis and Severity Prediction Using Machine Learning," in *Proceedings of the IEEE Bombay Section Signature Conference (IBSSC)* (IEEE, 2022), 1–6.

17. E. Kuşkapan, M. A. Sahraei, M. K. Çodur, and M. Y. Çodur, "Pedestrian Safety at Signalized Intersections: Spatial and Machine Learning Approaches," *Journal of Transport and Health* 24 (2022): 101322, https://doi.org/10.1016/j.jth.2021.101322.

18. P. Wu, T. Chen, Y. D. Wong, X. Meng, X. Wang, and W. Liu, "Exploring Key Spatio-Temporal Features of Crash Risk Hot Spots on Urban Road Network: A Machine Learning Approach," *Transportation Research Part A: Policy and Practice* 173 (2023): 103717, https://doi.org/10.1016/j.tra.2023.103717.

19. M. Ijaz, M. Zahid, and A. Jamal, "A Comparative Study of Machine Learning Classifiers for Injury Severity Prediction of Crashes Involving Three-Wheeled Motorized Rickshaw," *Accident Analysis and Prevention* 154 (2021): 106094, https://doi.org/10.1016/j.aap.2021.106094.

20. P. Infante, G. Jacinto, A. Afonso, et al., "Comparison of Statistical and Machine-Learning Models on Road Traffic Accident Severity Classification," *Computers* 11, no. 5 (2022): 80, https://doi.org/10.3390/computers11050080.

21. S. L. Lee, "Assessing the Severity Level of Road Traffic Accidents Based on Machine Learning Techniques," *Advanced Science Letters* 22, no. 10 (2016): 3115–3119, https://doi.org/10.1166/asl.2016.8006.

22. H. Nguyen, C. Cai, and F. Chen, "Automatic Classification of Traffic Incident's Severity Using Machine Learning Approaches," *IET Intelligent Transport Systems* 11, no. 10 (2017): 615–623, https://doi.org/10.1049/iet-its.2017.0051.

23. A. Tortum and A. Atalay, "Spatial Analysis of Road Mortality Rates in Turkey," *Proceedings of the Institution of Civil Engineers-Transport* 168, no. 6 (2015): 532–542, https://doi.org/10.1680/jtran.14.00029.

24. S. J. Choi, J. Jiao, and A. Karner, "Tracing the Effects of COVID-19 on Short and Long Bike-Sharing Trips Using Machine Learning," *Travel Behaviour and Society* 35 (2024): 100738, https://doi.org/10.1016/j.tbs.2024.100738.

25. M. Sangare, S. Gupta, S. Bouzefrane, S. Banerjee, and P. Muhlethaler, "Exploring the Forecasting Approach for Road Accidents: Analytical Measures With Hybrid Machine Learning," *Expert Systems with Applications* 167 (2021): 113855, https://doi.org/10.1016/j.eswa.2020.113855.

26. S. Sarkar, S. Vinay, R. Raj, J. Maiti, and P. Mitra, "Application of Optimized Machine Learning Techniques for Prediction of Occupational Accidents," *Computers and Operations Research* 106 (2019): 210–224, https://doi.org/10.1016/j.cor.2018.02.021.

27. Y. W. Wu and T. P. Hsu, "Mid-Term Prediction of At-Fault Crash Driver Frequency Using Fusion Deep Learning With City-Level Traffic Violation Data," *Accident Analysis and Prevention* 150 (2021): 105910, https://doi.org/10.1016/j.aap.2020.105910.

28. A. Theofilatos, A. Ziakopoulos, E. Papadimitriou, and G. Yannis, "How Many Crashes Are Caused by Driver Interaction With Passengers? A Meta-Analysis Approach," *Journal of Safety Research* 65 (2018): 11–20, https://doi.org/10.1016/j.jsr.2018.02.001.

29. D. Santos, J. Saias, P. Quaresma, and V. B. Nogueira, "Machine Learning Approaches to Traffic Accident Analysis and Hotspot Prediction," *Computers* 10, no. 12 (2021): 157, https://doi.org/10.3390/computers10120157.

30. C. Ma, Y. Peng, L. Wu, X. Guo, X. Wang, and X. Kong, "Application of Machine Learning Techniques to Predict the Occurrence of Distraction-Affected Crashes With Phone-Use Data," *Transportation Research Record* 2676, no. 2 (2022): 692–705, https://doi.org/10.1177/03611981211045371.

31. H. Nassiri and A. Mohamadian, "Prediction of Roadway Accident Frequencies: Count Regressions Versus Machine Learning Models," *Scientia Iranica* 21, no. 2 (2014): 263–275.

32. T. Bokaba, W. Doorsamy, and B. S. Paul, "Comparative Study of Machine Learning Classifiers for Modelling Road Traffic Accidents," *Applied Sciences* 12, no. 2 (2022): 828, https://doi.org/10.3390/app12020828.

33. J. Xu, K. Guo, and P. Z. Sun, "Driving Performance Under Violations of Traffic Rules: Novice vs. Experienced Drivers," *IEEE Transactions on Intelligent Vehicles* 7, no. 4 (2022): 908–917, https://doi.org/10.1109/TIV.2022.3200592.

34. A. J. Khattak, N. Ahmad, B. Wali, and E. Dumbaugh, "A Taxonomy of Driving Errors and Violations: Evidence From the Naturalistic Driving Study," *Accident Analysis and Prevention* 151 (2021): 105873, https://doi.org/10.1016/j.aap.2020.105873.

35. C. A. C. Ortega, M. A. Mariscal, W. Boulagouas, S. Herrera, J. M. Espinosa, and S. García-Herrero, "Effects of Mobile Phone Use on Driving Performance: An Experimental Study of Workload and Traffic Violations," *International Journal of Environmental Research and Public Health* 18, no. 13 (2021): 7101, https://doi.org/10.3390/ijerph18137101.

36. "General Structure of Erzurum Province," Erzurum Metropolitan Municipality, accessed December 21, 2023, https://www.erzurum.bel.tr/.

37. "General Directorate of Security," Traffic Accident statistics, accessed January 11, 2024, https://www.kgm.gov.tr/sayfalar/kgm/sitetr/trafik/trafikkazalariozeti.aspx.

38. "Accident Statistics by Province," Turkish Statistical Institute, accessed February 24, 2024, https://data.tuik.gov.tr/Bulten/Index?p=Karayolu-Trafik-Kaza-Istatistikleri-2022-49513.

39. "Highway Traffic Law," General Directorate of Highways, accessed January 13, 2024, https://www.mevzuat.gov.tr/mevzuatmetin/1.5.2918.pdf.

40. I. H. Sarker, "Machine Learning: Algorithms, Real-World Applications and Research Directions," *SN Computer Science* 2, no. 3 (2021): 160, https://doi.org/10.1007/s42979-021-00592-x.

41. W. Strielkowski, A. Vlasov, K. Selivanov, K. Muraviev, and V. Shakhnov, "Prospects and Challenges of the Machine Learning and Data-Driven Methods for the Predictive Analysis of Power Systems: A Review," *Energies* 16, no. 10 (2023): 4025, https://doi.org/10.3390/en16104025.

42. X. Zhang and Q. Song, "Predicting the Number of Nearest Neighbors for the k-NN Classification Algorithm," *Intelligent Data Analysis* 18, no. 3 (2014): 449–464, https://doi.org/10.3233/IDA-140650.

43. C. C. Chang and C. J. Lin, "LIBSVM: A Library for Support Vector Machines," *ACM Transactions on Intelligent Systems and Technology* 2, no. 3 (2011): 1–27, https://doi.org/10.1145/1961189.1961199.

44. T. Chen, S. Ju, F. Ren, M. Fan, and Y. Gu, "EEG Emotion Recognition Model Based on the LIBSVM Classifier," *Measurement* 164 (2020): 108047, https://doi.org/10.1016/j.measurement.2020.108047.

45. M. Yılmaz and F. Tosunoğlu, "Non-Stationary Low Flow Frequency Analysis Under Climate Change," *Theoretical and Applied Climatology* 155, no. 8 (2024): 7479–7497.

46. F. Alam, R. Mehmood, I. Katib, and A. Albeshri, "Analysis of Eight Data Mining Algorithms for Smarter Internet of Things (IoT)," *Procedia Computer Science* 98 (2016): 437–442, https://doi.org/10.1016/j.procs.2016.09.068.

47. H. Xiong, M. Li, T. Jiang, and S. Zhao, "Classification Algorithm Based on NB for Class Overlapping Problem," *Applied Mathematics and Information Sciences* 7, no. 2 (2013): 409–415.

48. S. Afzal, B. M. Ziapour, A. Shokri, H. Shakibi, and B. Sobhani, "Building Energy Consumption Prediction Using Multilayer Perceptron Neural Network-Assisted Models; Comparison of Different Optimization Algorithms," *Energy* 282 (2023): 128446, https://doi.org/10.1016/j.energy.2023.128446.

49. E. B. Baum, "On the Capabilities of Multilayer Perceptrons," *Journal of Complexity* 4, no. 3 (1988): 193–215, https://doi.org/10.1016/0885-064X(88)90020-9.

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

50. M. Yilmaz, F. Tosunoglu, and N. H. Kaplan, "Evaluation of Trends and Dominant Modes in Maximum Flows in Turkey Using Discrete and Additive Wavelet Transforms," *Journal of Hydrologic Engineering* 25, no. 11 (2020): 05020037.

51. G. Biau and E. Scornet, "A Random Forest Guided Tour," *Tested* 25 (2016): 197–227, https://doi.org/10.1007/s11749-016-0481-7.

52. M. Cerrada, G. Zurita, D. Cabrera, R. V. Sánchez, M. Artés, and C. Li, "Fault Diagnosis in Spur Gears Based on Genetic Algorithm and Random Forest," *Mechanical Systems and Signal Processing* 70–71 (2016): 87–103, https://doi.org/10.1016/j.ymssp.2015.08.030.

53. E. Borgonovo, "Sensitivity Analysis," in *Tutorials in Operations Research* (INFORMS, 2023), 52–81, https://doi.org/10.1287/educ.2023.0266.contrib.

54. W. Tian, "A Review of Sensitivity Analysis Methods in Building Energy Analysis," *Renewable and Sustainable Energy Reviews* 20 (2013): 411–419, https://doi.org/10.1016/j.rser.2012.12.014.

55. F. Ferretti, A. Saltelli, and S. Tarantola, "Trends in Sensitivity Analysis Practice in the Last Decade," *Science of the Total Environment* 568 (2016): 666–670, https://doi.org/10.1016/j.scitotenv.2016.02.133.

56. L. Lilburne and S. Tarantola, "Sensitivity Analysis of Spatial Models," *International Journal of Geographical Information Science* 23, no. 2 (2009): 151–168, https://doi.org/10.1080/13658810802094995.

57. F. Pianosi, K. Beven, J. Freer, et al., "Sensitivity Analysis of Environmental Models: A Systematic Review With Practical Workflow," *Environmental Modelling and Software* 79 (2016): 214–232, https://doi.org/10.1016/j.envsoft.2016.02.008.

58. C. Xu and G. Z. Gertner, "Uncertainty and Sensitivity Analysis for Models With Correlated Parameters," *Reliability Engineering and System Safety* 93, no. 10 (2008): 1563–1573, https://doi.org/10.1016/j.ress.2007.06.003.

17519578, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/itr2.70057 by Readcube (Labtiva Inc.), Wiley Online Library on [03/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License